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EEG-Based Mobile Robot Control Through an Adaptive Brain–Robot Interface

Vaibhav Gandhi, Girijesh Prasad, Damien Coyle, Laxmidhar Behera, and Thomas Martin McGinnity

***Abstract*—A major challenge in two-class brain–computer interface (BCI) systems is the low bandwidth of the communication channel, especially while communicating and controlling assistive devices, such as a smart wheelchair or a telepresence mobile robot, which requires multiple motion command options in the form of forward, left, right, backward, and start/stop. To address this, an adaptive user-centric graphical user interface referred to as the intelligent adaptive user interface (iAUI) based on an adaptive shared control mechanism is proposed. The iAUI offers multiple degrees-of-freedom control of a robotic device by providing a continuously updated prioritized list of all the options for selection to the BCI user, thereby improving the information transfer rate. Results have been verified with multiple participants controlling a simulated as well as physical pioneer robot.**

***Index Terms*—Brain–computer interface (BCI), graphical user interface, motor imagery, wheelchair/robot.**

I. Introduction

Brain–computer interface (BCI) technology provides a means of communication that allows individuals with severely impaired movement to communicate with assistive devices using the electroencephalogram (EEG) or other brain signals. The output signal from a BCI is limited and may not facilitate direct interfacing to technologies that are controlled using conventional means. For instance, with a simple 2-class BCI system, there are normally only two output commands e.g., a left hand motor imagery (MI) or a right hand/foot MI, for every trial rendering control of assistive devices such as a smart wheelchair or a telepresence mobile robot, which requires multiple motion commands, a significant challenge. A possible option is to use a multiple class BCI, for example, three, four, or an eight-class BCI. However, the classification accuracy progressively reduces as the number of classes increase [1]. In addition, more mental tasks require added complexity in terms of protocol design [2]. Other BCI modalities such as SSVEP or P300 may involve flickering displays which may not suit some BCI users [3]. Hence, this paper proposes to devise a consistently extendable GUI to use a two-class MI BCI to perform a multitask robotic control problem.

Many designs for brain-controlled wheelchair (BCW) are available in the literature [4]–[8]. However, some of these approaches are primarily autonomous or are automatic-forward movement-based designs where the user can only control a left or right hand movement without being able to stop the mobile robot. Therefore, an intelligent adaptive user interface (iAUI) within the framework of the adaptive shared control BCI system is proposed in this paper.

MI is used in this paper to control the proposed interface using the synchronous mode of BCI operation (cue based and computer driven). The noisy EEG signals acquired from the user in the robotic arena (real-world environment) are filtered using a recurrent quantum neural network (RQNN)[1] method [9], [10] before forwarding to feature extraction and task classification stages. There are seven sections in this paper. Section II details the proposed iAUI architecture, flowchart and an example scenario. Section III explains the performance quantifiers for the interface. Section IV describes the performance evaluation using these quantifiers under 100% BCI accuracy assumption and also compares the same with contemporary designs. Sections V and VI detail the real-time operation of the iAUI for robot control tasks in a simulated and a physical robotic arena, respectively. Section VII concludes the paper.

II. Intelligent Adaptive User Interface (iAUI)

A. Basic Design

The monitor module (MM) in Fig. 1 shows the user interface in its basic form. It involves selecting the movement tasks, left, right, forward, backward, halt, or transferring control to another GUI via main using just the two-class MI, i.e., left hand or right hand MI. The selection arrow points to the two available choices in every trial. For instance in Fig. 1, the user can select the forward command with a left hand MI or the right command with a right hand MI. If the user does not perform any MI during the trial period then a no-control (NC) state is assumed and the selection arrow moves down to the next selection option. The user can then perform one of the two mental imageries but with the available choices being left movement or backward movement with reference to the robotic device. Again, if the user does not perform either MI, the selection pointer moves to the next available options. The

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V. Gandhi is with the School of Science and Technology, Middlesex University, London NW4 4BT, U.K. (e-mail: v.gandhi@mdx.ac.uk).

G. Prasad, D. Coyle, and T. M. McGinnity are with the Intelligent Systems Research Centre, University of Ulster, Londonderry BT48 7JL, U.K. (e-mail: g.prasad@ulster.ac.uk; dh.coyle@ulster.ac.uk; tm.mcginnity@ulster.ac.uk).

L. Behera is with the Department of Electrical engineering, Indian Institute of Technology Kanpur, Kanpur 208016, India (e-mail: lbehera@iitk.ac.in).

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[1]The RQNN approach is based on the concepts from quantum mechanics. The RQNN is constructed using a layer of neurons within the neural network framework that recurrently computes a time-varying probability density function (pdf) for the measurement of the observed signal with the Schrodinger Wave Equation (SWE) playing a major part.

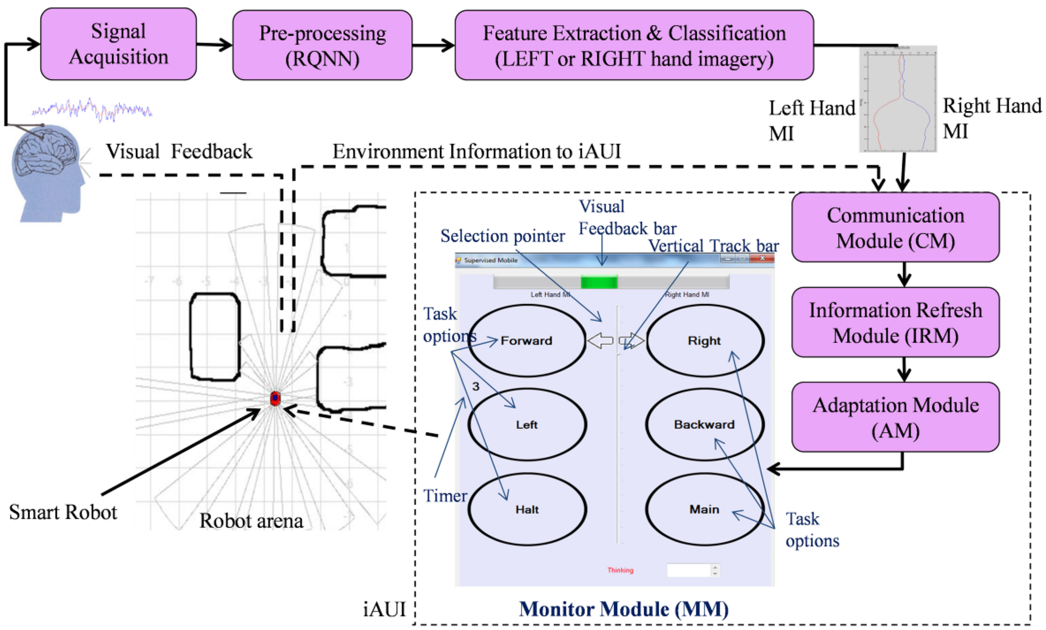

Fig. 1. User screen within the framework of the iAUI and the complete BCI loop. The selection arrow indicates the user of the two available options during any trial. If the arrow points to the options as forward and right, the user can issue the forward command by performing left hand MI. The vertical track bar and the timer indicate the user of the time when the selection arrow moves from one set of options to the next. The feedback bar gives sensorimotor feedback.

actual command to drive the robot is sent at an exact time-instant that is most suited to the BCI user [usually at 6 (or 4) s where the peak offline accuracy for a 7 (or 5) s trial is detected during offline analysis]. Thus, if the user intends to select the *n*th choice then a wait of the scan time of $t_0 = (n-1)t_s + t_s = nt_s$ is necessary where t_s is the trial time. If the value of t_0 exceeds T (the scan time for one complete scan cycle), then it means that the user failed/did not select the task in the first scan. The user then has to wait until the pointer again points to the desired task. The time required to select the first of the two options is t_s whereas the maximum time required to select the last two options in the first scan cycle is $3t_s$. However, the maximum selection time of a task can be reduced if the available options on the user interface can be appropriately reordered. This is the focus of the iAUI architecture [10].

B. iAUI Architecture

Fig. 1 also displays the iAUI architecture within the complete BCI setup. The acquired noisy EEG signal, contaminated particularly with motion artifacts in Robotics Laboratory, is filtered through a preprocessing block using a novel RQNN method [9], [10]. The class information (left hand or right hand movement imagery) from the features of the filtered EEG signal is sent to the iAUI. The iAUI is composed of four main modules namely the communication module (CM), the information refresh module (IRM), the adaptation module (AM) and the MM (front view of the iAUI) (Fig. 1). The CM communicates bi-directionally with the robotic device (receives sonar sensor values and issues commands) and unidirectionally with the BCI user (receives postprocessed class information). The IRM gathers information about the surrounding environment (through the CM) and interacts with the adaptation mechanism of the AM. The AM retains or modifies the existing rules and is responsible for the final adaptability of the MM. The adaptability of the MM refers to the process of reconfiguring the GUI after the BCI user issues a command or a scan cycle of the interface is completed without the user issuing any command. Thus, the commands that are offered to the BCI user (i.e., backward, forward, right, left, halt, and main) will be displayed on the MM such that the most likely command is placed at the top-most location ready for selection at the start of the scan cycle. The two options at the top-most location have the highest probability of being expected as a choice from the BCI user. These most likely options are the quickest to access and thereby reduce the decision-making time.

C. Control Flow of Interface

The flowchart in Fig. 2 shows the control flow of the interface with a typical trial time of 7 s. The command is issued by the BCI user at 6 s in the trial period and the controlled device issues the interface update feedback (through the CM) after 0.9 s. This small time interval is taken as an added measure to further increase the possibility of passing on the information about the change in the dynamic environment (when the mobile device is performing the commanded operation) to the user interface. The interface is allowed to adapt and update only in two cases; first, when the user sends a command to the device and secondly, when the entire interface scan cycle is completed without the BCI user issuing any command. The purpose of updating the interface after a complete scan cycle is to incorporate any changes that might have occurred within the dynamic environment during the complete scan cycle of $3{*}t_s$.

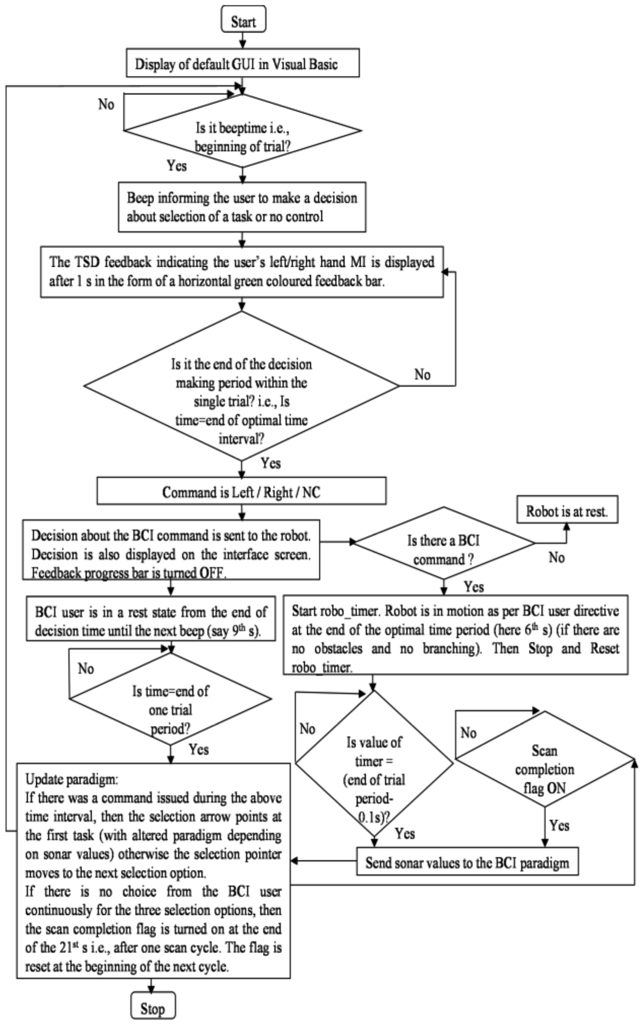

Fig. 2. Flowchart of the user interface.

D. iAUI Operation in Example Scenario

Fig. 3 displays a graphical view to understand the various adaptive forms of the interface using an example. The robotic arena is displayed as a visual scene on the right side while the GUI associating the user's mental imagination is displayed on the left side of Fig. 3(a)–(c).

Assume that the robot begins from a starting position marked as robot in Fig. 3(a) and is to be maneuvered toward the target position shown by an orange colored marker. The arena also has various obstacles as shown in the form of cluttered images. At start position in Fig. 3(a), the two most probable choices displayed are forward and right. The BCI user performs a left hand MI and issues the command forward. When the robot begins to move in the forward direction, the left and right hand sides of the robot get blocked and only the front and backward sides remain open [shown in Fig. 3(b)]. This information is sent to the interface in the form of sonar sensor values. Thus, the interface adapts immediately after the user's forward command and alters the first two probable choices as backward and forward. Thus, the user has an opportunity to select the forward and the backward choices in the first instance, as these are the most suitably available choices. In another situation shown in Fig. 3(c), the sonar sensor information sent to the iAUI suggests three probable openings for movement; forward, backward and left. However, the interface has the rules within the AM that gives higher priority to forward movement and subsequently to the right, left, and the backward movements. The backward movement is assigned least priority as it is assumed to be a least likely choice. Hence, the interface in Fig. 3(c) lists the probable options as left and forward.

Had there been no adaptability in the interface, the user is expected to issue NC command(s) to reach the second choice or third choice option in a static interface and then issue an appropriate command. The adaptability strategy thus saves issuance of additional commands in the form of an NC, which is a time equivalent to one trial time. Another major advantage of the adaptive interface is that even a least expected task (say, backward) is made available to the user at all stages. The purpose is to let the user have complete access to all the choice options (prioritized) i.e., user at the center of priority—user-centric design.

E. Autonomous Mobility Control Interface (MOB)

Fig. 4 displays the interface for autonomous control of the mobile robot (MOB). The selection of the choices is as per the approach discussed in the previous section. The BCI user can select a particular destination that may be displayed on the interface but by associating his/her MI in accordance with the position of the selection arrow. The mobile robot has the potential to reach the specified destination by utilizing an in-built obstacle avoidance technique and the predefined map of the robotic arena. The purpose of this interface is intended to guide the BCI user to reach the doorstep of a particular room or location (Fig. 5). Once the robot reaches this destination through autonomous navigation, the finer maneuvering can be implemented at the discretion of the BCI user through the commands within the supervised iAUI mode. Thus, the interface is designed to provide true independence to the BCI user.

III. Performance Quantifiers

BCW or mobile robot interface design performance [7], [8] is often analyzed in terms of mission time, concentration time, nominal time, and total cost for task completion. These measures can be made independent of the signal processing issues in BCI and can quantify the real assistance that a user gets by way of interface adaptation approach. The mission time is the time to select a destination or the target on the user interface plus the total traveling time needed for maneuvering the mobile robot to reach the target as interpreted in [4]. The concentration time is the mission time minus the relaxation period, i.e., the sum of the duration of MI for all trials. The nominal time is the minimal time required for the robot to reach the destination.

The interface presented in this paper is based on a synchronous MI BCI concept. Therefore, the interpretation of mission time as in [4] is true in the proposed paper only for the autonomous design where both the quantifiers, i.e., the time to

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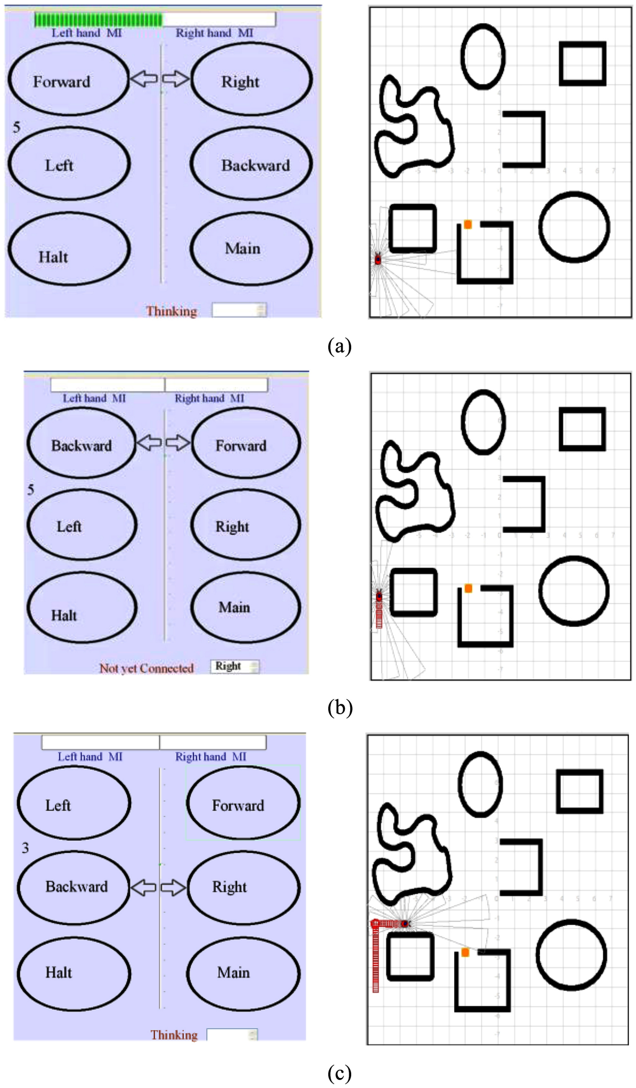

Fig. 3. Example to understand the adaptable nature of the iAUI. (a) Forward and right have higher priority than the backward and left. The forward command is sent by the BCI user through a left hand MI. (b) During motion, backward and forward have better accessibility, and hence, they are prioritized and repositioned accordingly. (c) After forward command, the interface updates by prioritizing forward and left as they become more accessible.

select the destination and the time for mobile robot travel are independent of each other. However, in the supervised (both fixed and adaptive) form of the interface the user can issue a command while the mobile robot is in motion, i.e., there is an overlap in both these quantifiers. Therefore, the mission time in this paper is simply the total time required to reach the target destination from the original position beginning with the time the first command is initiated (including the first trial time). The concentration time is calculated through the MI that is performed in a trial duration[2] (by excluding the trials with NC), i.e., mission time minus the relaxation period. To calculate the total cost for task completion, the parameters mission time ratio and the concentration time ratio

[2]The trial duration time may be of 5 or 7 s. However, the user performs actual MI for 4 s and the command is sent at the end of (trial duration-1) s.

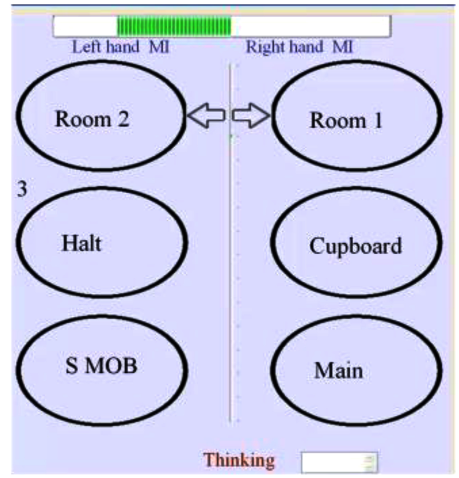

Fig. 4. Autonomous interface.

have been considered as in [4]. The nominal time is calculated separately for the supervised and the autonomous control interfaces because the travel path may vary with different interfaces

$$\text{Total cost} = \text{concentration time ratio} + \text{mission time ratio} \quad (1)$$

where

$$\text{Concentration time ratio} = \text{concentration time/nominal time}$$
$$\text{Missiontime ratio} = \text{mission time/nominal time.}$$

IV. Maneuvering Mobile Robot Under 100% BCI Accuracy Assumption

The evaluation of the interface can be explained by considering the diagram of a typical robotic arena within player-stage[3] [11] simulation shown in Fig. 5. Here, an ideal TSD with 100% CA is assumed. The main aim is to thus evaluate the capability of the interface and not of the accuracy of the BCI user that depends on several factors. Here, three different locations (marked in orange) are identified as Room 1, Room 2, and a Cupboard, and the robot located in the bottom left corner. The user is required to maneuver the robot to each of the three locations from the origin by using the adaptive, the nonadaptive and the autonomous interface. Fig. 5 also shows the mobile robot trail for one of the destination Room 2 by implementing the commands from the adaptive, nonadaptive and the autonomous interfaces. The performance of the interface is evaluated by measuring the time taken and the number of commands required to reach each of the three target locations from the original starting position of the robot.

A. Evaluating the Interfaces

Table I details the number of commands needed to reach the specified destination. Thirteen commands are required to

[3]The player-stage environment simulates the physical dynamics of the pioneer robot as well as the environment and thus facilitates an easy transition of the results to the real-world environment. Over 50 different research laboratories and institutions all around the world are currently involved in the active development of the player-stage [11].

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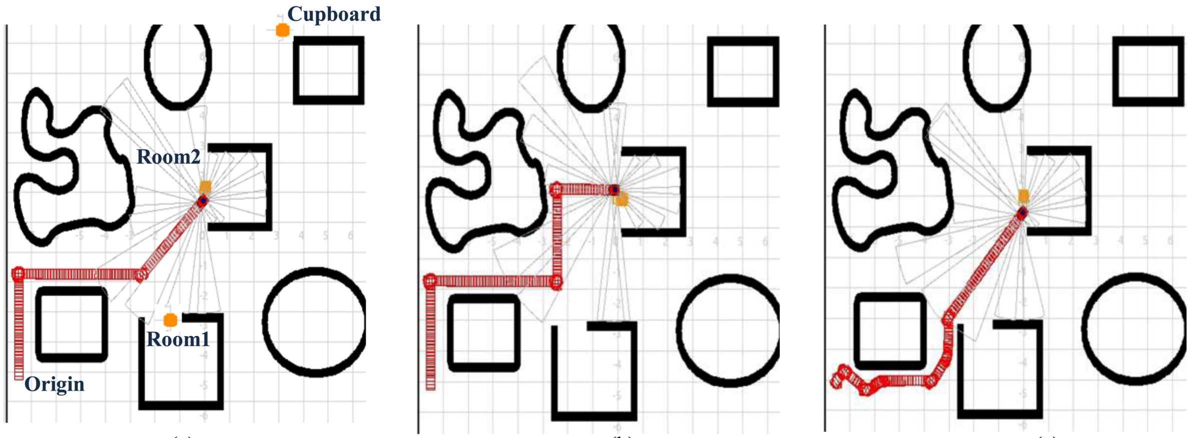

(a) (b) (c)

Fig. 5. Mobile robot trail for three destination targets using different interfaces. (a) Through adaptive interface. (b) Through nonadaptive interface. (c) Through autonomous interface.

reach Room 1 through the iAUI and the nonadaptive interface. Therefore, the concentration time is

$$\text{Concentration Time} = \text{number of MI commands} * \text{duration of MI in a single trial } 13*4 = 52s.$$

Similarly, for the autonomous interface design (Fig. 4), the command to select the task Room 1 or Room 2 can be sent through the first trial while the command to select the task cupboard can be sent through the second trial (albeit with one NC), thereby resulting in a concentration time of 4 s. In a similar way, the concentration time can be calculated for the other interface design(s) and destinations.

Table II lists each command sent from the interface. The number of single NC command required from the user with the adaptive interface (i.e., iAUI) is only one for all the three tasks (Room 1, Room 2, and cupboard) while the same action with the fixed interface is requiring up to 20 NC states. A single NC is required when the user intends to select a task that is available in the second or subsequent available options within the GUI. This suggests that the iAUI prioritizes the commands available to the user so that the user is preferably not required to perform NC and go to the next available choice. In addition, as shown in Table I, the total number of NCs required for all the three tasks has also reduced from 45 (with the nonadaptive interface) to 31 (with the adaptive interface), i.e., a gain of 14 trial times. Simultaneously, the total number of commands required from the BCI user for completing all the three tasks has also reduced from a likely number of 46 (with the nonadaptive interface) to 42 (with the adaptive interface). Both these reductions contribute to making the completion of the overall sequence more efficient using the adaptive interface.

Table III details the parameters required to calculate the total cost incurred in completing a task. The total cost with the adaptive interface (i.e., the iAUI) for all the three task locations is always much less compared to the fixed/static interface design [average is 1.98 (adaptive) versus 2.21 (fixed)] but more than the autonomous interface (average is 1.10).

However, a major requirement of autonomous designs is the need to have a stored map of the robotic arena and that of limited predefined tasks for user selection. On the contrary, a major advantage of the adaptive interface over the autonomous interface is the freedom for the user to select any desired task for the robotic movement but this incurs a higher cognitive load. Therefore, some form of a combined approach, involving switching between the interfaces may be a preferred method for real-time practical applications. This can be implemented through the main interface shown in Fig. 6. Here, SMOB represents supervised mobility control interface and MOB represents autonomous mobility control interface. The ARM and SARM are for robotic arm control applications which are not presented in this paper.

TABLE I

NUMBER OF COMMANDS REQUIRED TO CONTROL THE ROBOT IN AN UNSTRUCTURED ENVIRONMENT SHOWN IN FIG. 5

Destination	No. of commands to reach the specified destination (with No-Control)		
	Adaptive Interface	Non-adaptive Interface	Autonomous Interface
Room 1	13 / (07)	13 / (13)	01 / (13)
Room 2	09 / (07)	11 / (12)	01 / (17)
Cupboard	20 / (17)	22 / (20)	01 / (25)

B. Comparing Interfaces

The total cost in accomplishing a task with all the three forms of the interface is compared with the interface designs discussed in [4]–[8] (Table IV) by using the same cost criteria. A major limitation of the BCW by Rebsamen *et al.* [4] and MAIA [6] is that it uses prior knowledge about the location of the target. The BCW by Iturrate *et al.* [8] incurs a very high cost while the BCW by Satti *et al.* [5] does not have a command to stop the robot. Therefore, with these approaches, real-time BCW involving complex paths may not offer the real independence to the BCI user.

The average cost of the proposed approach is 1.98, 2.21, and 1.1 with the adaptive, nonadaptive, and autonomous interface design (Table III), respectively, that gives a comparable low

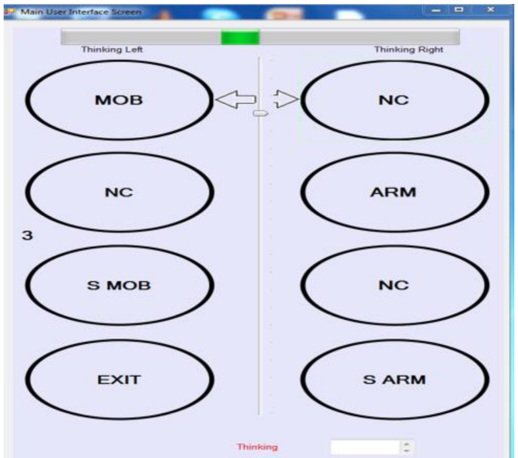

Fig. 6. Main interface.

cost without really compromising on the control choices. Compared to all the BCW methodologies discussed here, the autonomous interface based design proposed in this paper is the most cost-effective approach. However, it has a limitation in the form of a predefined map and a limited number of target destinations. In this respect, the iAUI proposed in this paper is a better choice as it gives complete freedom through supervisory control. However, this approach is not as cost-effective as the autonomous interface or the one proposed by Rebsamen *et al.* [4]. Therefore, it is more practical and appropriate to simultaneously utilize both the autonomous as well as the adaptive interfaces proposed in this paper for real-time applications. The approximate cost while utilizing a combination of both these interfaces will depend on the application, however, the actual freedom of managing tasks is available to the BCI user at all times.

V. Simulated Mobile Robot Control With MI

The iAUI has been utilized to maneuver the robotic device to the three destinations marked as Room 1, Room 2, and cupboard by using only the MI. Five subjects, all male in the age group of 23–35, took part in the investigation which was approved from the University of Ulster's Research Ethics Committee. Of these, three subjects were experienced while one had participated about 3 times in BCI experiments previously and one was naive. The EEG signals were acquired at a sampling frequency of 256 Hz using the gUSBamp dry electrode system from g.Tec [12]. The subjects were initially trained on a two-class training paradigm (60 trials), which displays either left or right arrow pointing continually for 4 s. There are 30 right hand and 30 left hand arrows being displayed in every run randomly. Each day, one EEG session training data thus collected was used to obtain Hjorth [13] and bandpower features for training the classifier using five-fold cross-validation (CV). For mobility control, each subject was given a maximum duration of 12 min to reach any specific destination. If the subject did not reach the destination within this duration or if the subject did not feel at ease during a particular attempt (either due to tiredness or being unable to concentrate) then it was aborted and a new attempt was initiated.

TABLE II
Commands Sent to Control the Robot in an Unstructured Environment Shown in Fig. 5

Adaptive			Non-Adaptive		
Room 1	Room 2	Cupboard	Room 1	Room 2	Cupboard
F	F	F	F	F	F
3 NC	3 NC	3 NC	3 NC	3 NC	3 NC
R	R	R	NC	NC	NC
F	F	F	R	R	R
3 NC	3 NC	3 NC	F	F	F
R	F	F	3 NC	3 NC	3 NC
F	L	L	F	F	F
L	F	F	NC	NC	NC
L	F	F	R	L	L
F	F	L	F	F	F
F	F	F	NC	F	3 NC
R	NCW*	R	L	NC	NC
F		F	F	R	R
L		3 NC	NC	NC	NC
F		R	L	R	R
NCW*		F	F	F	F
		3 NC	NC	F	F
		F	R	2NCW*	NC
		L	NC		R
		F	L		F
		F	F		NC
		3 NC	NCW*		L
		F			F
		NC			NC
		L			R
		F			F
		NCW*			F
					NC
					L
					F
					NC
					L
					F
					NC
					R
					NCW*
13 / 7 NC	9 / 7 NC	20 / 17 NC	13 / 13 NC	11 / 12 NC	22 / 20NC

* NC Wait from user awaiting the implementation of the last command when the mobile robot is about to reach the destination.

Fig. 7 shows the robot trail where the simulated robot was maneuvered from the origin to the destination (orange icon) and the user performing the MI (subject V01) in accordance with the iAUI (see [14] for a link to the video showing robot control through MI for all the subjects). Table V lists the performance measure values for all the subjects while trying to complete the three tasks. The overall cost for maneuvering is larger than that obtained using the zero error assumption (Table III). This is as expected because during the issuance of commands through MI related EEG signals, there may be considerable errors from the BCI user as well as from the signal processing. This being in real-time and the knowledge of the user's class label being unavailable, it is not possible to exactly know the amount of error.

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TABLE III
PERFORMANCE MEASURE TO CONTROL THE ROBOT IN AN UNSTRUCTURED ENVIRONMENT SHOWN IN FIG. 5

Destination	BCW (for Room 1)			BCW (for Room 2)			BCW (for cupboard)		
	Adaptive Interface	Non-adaptive Interface	Autonomous Interface	Adaptive Interface	Non-adaptive Interface	Autonomous Interface	Adaptive Interface	Non-adaptive Interface	Autonomous Interface
nominal time	72	73	66	65	83	86	128	134	121
mission time	100	130	70	80	115	90	185	210	130
Mission time ratio	1.38	1.78	1.06	1.23	1.38	1.04	1.44	1.56	1.07
Concentration time	52	52	4	36	44	4	80	88	4
Concentration time ratio	0.72	0.71	0.06	0.55	0.53	0.04	0.62	0.66	0.03
Total Cost	2.1	2.49	1.12	1.78	1.91	1.08	2.06	2.22	1.10

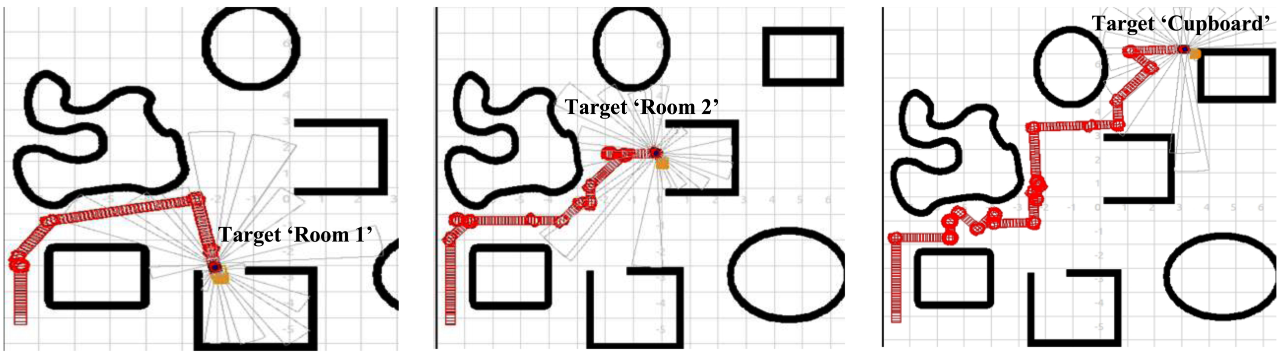

Fig. 7. Mobile robot trail (simulated player-stage environment) for the three destination targets using the iAUI for subject V01 (see [14] for a link to video).

TABLE IV
EVALUATION OF STRATEGIES TO CONTROL A WHEELCHAIR WITH BCI (PARTIALLY REPRODUCED FROM [4] AND [5])

	Satti		Rebsamen		MAIA	Toyota	Iturrate	
	Self-paced	Synchronous	No false stop	Some false stops			Complex environment	open space
Number of false stops	NA	NA	0	1.21	NA	NA	NA	NA
Nominal time (s)	88	88	100	100	100	17	24	64
Mission time (s)	115.19	228	112	128	200	22.88	571	659
Mission time ratio	1.3	2.59	1.13	1.28	2	1.35	25	10.3
Concentration time (s)	15	96	12.6	28.3	200	22.88	447	439
Concentration time ratio	0.17	1.09	0.13	0.28	2	1.35	18.6	6.8
Total cost	1.47	3.68	1.26	1.56	4	2.7	43.6	17.1

VI. PHYSICAL MOBILE ROBOT CONTROL WITH MI

Three subjects, all male in the age group of 21–35 attempted to maneuver the mobile robot in the robotic arena in the Cognitive Robotics Laboratory at the Intelligent Systems Research Center (ISRC) through the iAUI (Fig. 8) (see [14] for video) under approval from the University of Ulster's Research Ethics Committee. Of the three subjects, two were highly experienced while one had only limited experience. As discussed in the previous section, at the beginning of every session, the subjects performed one training run for setting up the classifier for the online model. The RQNN preprocessing technique [9], [10] was used for filtering the EEG signals before obtaining the features for the classification process. Table 6 indicates the performance evaluation in terms of total cost for each subject while maneuvering the mobile robot to the specified target locations Target 1 and Target 2. Fig. 8 shows the robot trail while reaching the destination Target 2 in the robotic arena for subject V01.

TABLE V
PERFORMANCE EVALUATION FOR REAL-TIME CONTROL OF THE ROBOT IN AN UNSTRUCTURED ENVIRONMENT SHOWN IN FIG. 5

Parameter	Subjects (Room 1)				
	V01*	C02*	K03	G04	I05
nominal time	72	72	72	72	72
mission time	115	415	371	630	756
Mission time ratio	1.59	5.76	5.15	8.75	10.50
Concentration time	80	172	92	164	192
Concentration time ratio	1.11	2.38	1.27	2.27	2.66
Total Cost	2.7	8.14	6.42	11.02	13.16

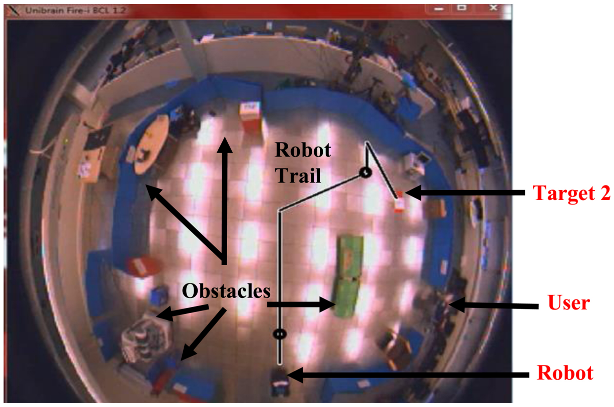

Fig. 8. Mobile robot trail (robotic arena) for the destination Target 2 using the iAUI for subject V01 (see [14] for a link to the video).

TABLE VI
PERFORMANCE EVALUATION FOR ROBOT CONTROL WITHIN THE ARENA SHOWN IN FIG. 8

Parameter	Subjects				
	Target 1		Target 2		
	V01	K03	V01	K03	S04
nominal time	37	37	50	50	50
mission time	77	315	140	462	441
Mission time ratio	2.08	8.51	2.8	9.24	8.82
Concentration time	40	64	68	144	140
Concentration time ratio	1.08	1.72	1.36	2.88	2.80
Total Cost	3.16	10.23	4.16	12.12	11.62

VII. CONCLUSION

This paper has presented real-time implementation of a novel iAUI design for a mobile robot control task. The major advantage with the iAUI is the user-centric design that presents all the control options to the BCI user at all times. The complete BCI system, including the RQNN technique (for EEG filtering) and the user-centric iAUI (for enhancing the bandwidth) were implemented for the robot control task in the physical environment. Most of the subjects reached the targets on the first or second attempt and were easily acquainted with the adaptive interface as the sessions progressed. However, better control as shown with the 100% BCI accuracy assumption can be achieved with more training on the paradigm. The proposed interface designs have the potential to provide true independence to the BCI user with a combination of autonomous and adaptive designs while not compromising much on the overall cost for the device control task. The simple multicircle design of the presented GUI can consistently and seamlessly be used for control through hybrid BCIs involving multimodalities, such as eye-tracker and ERP-based BCIs, and will be explored further in future.

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